Software Engineering

Trends in Class Decisions during Transitions in Myoelectric Control

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1 Focus

The purpose of this work is to develop a tool that collates and displays classifier decisions during transitions from one class to another in myoelectric control, aiming to identify common trends in classifier behavior. The motivation behind this research stems from the observation that while classifiers demonstrate high accuracy when trained and cross-validated offline using electromyography (EMG) data, their performance often does not translate to the same level of effectiveness when measured through usability metrics in controlling EMG-based assistive devices, such as myoelectric prostheses [1].

One plausible explanation for this performance discrepancy is that classifiers are typically trained using data collected during steady state contractions for each individual class [2]. However, real-world scenarios involving the use of assistive devices frequently involve dynamic contractions, including transitions from one class to another. Unfortunately, there has been limited research conducted to investigate the effects of this incongruence, creating a gap in our understanding [2]. Therefore, this work aims to address this gap and explore the impact of transitions on classifier performance in myoelectric control.

The existing literature in this field is scarce, and various aspects need to be explored to bridge this knowledge gap. Previous studies have proposed rejection techniques to ignore transition regions [3]. However, these techniques predominantly rely on decision confidence, and classifiers often exhibit high confidence even in incorrect decisions, particularly during transitions [3]. Other research efforts have focused on studying the transition problem and its implications, including challenges associated with training classifiers to include transitions as separate classes and the assignment of labels in training [4]. These challenges arise due to the large number of classes required for training, considering that each transition would need to be adequately represented.

In light of these considerations, our goal was to investigate the behavior of classifiers trained with steady state data when tested with dynamic contractions, with a specific focus on analyzing the classifier decisions during transition regions. By developing a tool that collates and displays classifier decisions during these transitions, we aimed to identify common trends and gain insights into the classifier's behavior in dynamic contractions. The analysis of classifier decisions in transition regions can provide valuable information about the challenges and limitations of current classifier approaches, ultimately leading to improvements in the design and implementation of EMG-based assistive devices.

In this paper, we present the development of a graphical user interface (GUI) that enables the visualization and analysis of classifier decisions on EMG data during transition regions. The GUI provides researchers and developers with the means to examine uncertain frames and their predicted movements, facilitating the identification of patterns and trends in the classifier's decisions during transitions. By investigating these transition regions, we aim to shed light on the challenges and limitations associated with classifier performance in assistive device applications. Through this analysis, we hope to contribute to the development of improved usability metrics and enhance the functionality and user experience of EMG-based assistive devices.

Overall, this work strives to bridge the gap between offline classifier performance and real-time control in dynamic contractions. By studying the behavior of classifiers during transitions and identifying common trends, we seek to enhance our understanding of the challenges associated with classifier performance in assistive device applications. Through this investigation, we aim to pave the way for improvements in usability metrics and foster advancements in the design and implementation of EMG-based assistive devices.

2 Investigation

2.1 Tool Development

The development of the tool involved implementing a graphical user interface (GUI) using Python to visualize and analyze the predictions made by a classifier on electromyography (EMG) data during transitions between movement classes. The goal was to create a user-friendly tool that enables researchers and developers to gain insights into the behavior of the classifier during dynamic contractions, particularly during transition regions.

The GUI was built using the popular PyQt Python library, which provided the foundation for creating a visually appealing and interactive interface for users. These PyQt libraries allowed for the creation of tabular representations of uncertain frames during transition regions. The tables were generated dynamically based on the classifier's predictions, displaying the transitions between movement classes and the corresponding uncertainties. The GUI provided interactive features, such as the ability to toggle between different table formats and navigate through the data for individual participants.

To handle the data processing, the tool utilized Python's data manipulation and numerical computing library, NumPy. This library allowed for efficient loading and manipulation of the EMG data collected from participants. The tool provided the option to load individual participant data or aggregate data from multiple participants, enabling users to gain insights from both specific cases and overall trends.

Throughout the development process, Python's modular and extensible nature facilitated the integration of various components, ensuring a cohesive and functional tool. The use of Python for the development of this tool offered flexibility, ease of implementation, and access to a rich ecosystem of libraries and tools, which contributed to the overall success of the project.

The development of the tool leveraged Python's strengths in data manipulation, and data visualization to create a robust and user-friendly interface for viewing classifier decisions during transition regions in myoelectric control. The combination of Python's libraries and the carefully designed GUI resulted in a powerful tool that empowers researchers and developers in gaining valuable insights into the behavior of classifiers and improving the usability metrics of EMG-based assistive devices.

2.2 Experiment

2.2-a Data Set

The Raghu Dataset was made available by Shriram Raghu and consists of 43 sub- jects performing 7 classes of movement. Surface electromyography (sEMG) signals were recorded using six bipolar electrodes placed around the forearm, using a Delsys Trigno System. The signals were sampled at 2kHz with a 16-bit Analog-To-Digital converter [2]. The position of the hand was simultaneously recorded using a Leap Motion Controller to serve as ground truth for identifying transition regions.

For the training and testing protocol, participants performed ramp contractions followed by a steady-state contraction in different hand positions. The classes included Wrist Flexion (WF), Wrist Extension (WE), Wrist Pronation (WP), Wrist Supination (WS), Chuck Grip (CG), Hand Open (HO), and No Movement (NM). Each participant completed five trials, and the training data consisted of five repetitions of each class.

The test records involved continuous transitions from one class to another, generating 42 transitions in total (7 classes x 6 transitions). Participants were instructed to move randomly from one contraction to another and hold each contraction in steady state for 3 seconds. The Leap Motion position data was used to identify the bounds of transition regions based on hand orientation vector velocity, with a threshold to accommodate random fluctuations. Each participant completed six trials.

The study compared different Decision Stream Quality Improvement (DSQI) algorithms. The training and test records were segmented into overlapping frames of 160ms length with a 16ms increment. The LSF4 feature set was extracted from each frame. Three classifiers were trained: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM).

2.2-b Classification

LDA (Linear Discriminant Analysis) is a supervised learning algorithm used for classification tasks. It assumes that the data follows a Gaussian distribution and aims to find a linear combination of features that maximizes the separation between different classes [5]. LDA projects the data onto a lower-dimensional space while preserving the class separability. It computes class centroids and scatter matrices to determine the optimal projection direction. LDA is widely used in various fields, including pattern recognition, image processing, and bioinformatics.

To make predictions, LDA applies Bayes' rule, which involves calculating the posterior probability of a sample belonging to each class given its observed features [6]. The class with the highest posterior probability is then assigned to the sample. To perform this calculation, LDA uses the estimated parameters of the Gaussian distributions along with the prior probabilities of the classes, which can be determined from the training data.

LDA is a widely used classifier due to its simplicity and interpretability. It serves as a popular baseline model for comparison with more complex classifiers. Although LDA assumes linearity and the Gaussian distribution of data, it can still provide effective classification results in many practical scenarios.

2.2-c Collation

A graphical user interface (GUI) that visualizes the predictions made by a classifier on EMG data was developed in python. The purpose of the GUI is to analyze the classifier's behaviour during transition regions where movements shift from one class to another.

The GUI allows the user to load the previously collected data, as mentioned in section 2.2-a. The GUI identifies frames with lower confidence or uncertainty in their predictions. These uncertain frames are observed during transitions between movement classes. The data is loaded viewing all data collected from each participant, and the option is given to view individual data. When viewing individual participant data, the user will have the option to navigate to the preceding and proceeding data, while also having the option to select a participant's data from a dropdown list, or to type the desired participant into a search box.

The GUI displays uncertain frames and their predicted movements in a tabular format. These tables enable users to analyze the classifier's decisions during transition regions and identify patterns or trends. Each table represents the frames of uncertainty during the transition from one state to all other states. The format of each table is 6x8, with rows representing transitions between states and columns representing the possible states. The last column shows the total number of frames of uncertainty in each transition. Additionally, users can choose to view the table in a 7x8 format, which ensures consistency across all tables. In this format, a new row is added to indicate that there is no possible transition from the start state to itself, and it is displayed in grey to distinguish it from other rows.

Figure 1: Graphical User Interface with Loaded Data

By utilizing this GUI, researchers and developers can gain insights into the classifier's behavior during dynamic contractions and specifically focus on the predictions made during transition regions. Its ability to identify uncertain frames and present them in tabular format facilitated the identification of patterns and trends, aiding in the understanding of the classifier's behavior. The insights gained from this analysis contribute to the improvement of usability metrics in EMG-based assistive devices, furthering their applicability and impact in the field.

2.2-d Results and Discussion

The analysis revealed that during transitions, classifiers often exhibit high confidence even in incorrect decisions. This finding highlights the need for improved techniques to handle transitions and mitigate the impact of misclassifications. The GUI facilitated the identification of uncertain frames, enabling researchers to focus on these critical decision points and develop strategies to improve classifier performance during transitions.

Furthermore, the GUI allowed for the examination of common trends in classifier behavior during transition regions. Patterns such as increased uncertainty in specific movement transitions or consistent misclassifications were observed, providing valuable insights for further research and algorithmic improvements. Researchers can utilize this information to refine the training process, augment feature selection, or explore alternative classification algorithms that better handle transition scenarios.

The ability to visualize and analyze classifier decisions in transition regions also revealed the impact of transition-related challenges on usability metrics for EMG-based assistive devices. By understanding the behavior of classifiers during dynamic contractions, researchers can identify areas for improvement and develop more accurate and reliable metrics to assess the performance of these devices in real-world scenarios.

The GUI's ability to provide a comprehensive view of classifier behavior during dynamic contractions enables researchers to make informed decisions about algorithm selection, feature engineering, and system calibration. By leveraging these insights, future studies can focus on developing advanced classification algorithms that are specifically tailored to address the challenges associated with transitions, leading to improved control and usability of EMG-based assistive devices.

3 Contributions

This work makes significant contributions to the field of myoelectric control by developing a GUI that collates and displays classifier decisions during transitions in myoelectric control. This tool facilitates the analysis of patterns and trends in the behavior of classifiers during transition regions, allowing researchers to gain a more comprehensive understanding of the data being collected and processed.

The GUI serves as a user-friendly interface for researchers and developers to gain insights into the behavior of classifiers during dynamic contractions, where transitions between movement classes occur. By visualizing the classifier's decisions in tabular format, the tool allows for the identification of patterns in levels of uncertainty, enabling researchers to better understand the challenges and limitations associated with classifier performance during transitions.

By investigating the behavior of classifiers during dynamic contractions, specifically during transition regions, this work aims to bridge this gap and provide a deeper understanding of the challenges faced in real-world scenarios. Moreover, this work contributes to the development of improved usability metrics for EMG-based assistive devices. The ability to analyze patterns and uncertainties during transitions provides valuable information that can lead to advancements in usability metrics, ultimately enhancing the functionality and user experience of EMG-based assistive devices.

4 References

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